31st European Microwave Conference Proceedings, vol. 2, pp. 229-232, London, ENGLAND, Sep. 2001.

ARTIFICIAL NEURAL NETWORK MODELING FOR IMPROVED ON-WAFER LINE-REFLECT-MATCH CALIBRATIONS*

Jeffrey A. Jargon[1] and K. C. Gupta[2]

[1]National Institute of Standards and Technology
RF Electronics Group, 325 Broadway, Boulder, CO 80303 USA
Tel 303.497.3596 | Fax 303.497.3970 | E-mail: jargon@boulder.nist.gov

[2]Center for Advanced Manufacturing and Packaging of
Microwave, Optical, and Digital Electronics (CAMPmode)
University of Colorado at Boulder, Boulder, CO 80309

ABSTRACT

We model a load using an artificial neural network (ANN) to improve an on-wafer line-reflect-match (LRM) calibration of a vector network analyzer (VNA). The ANN is trained with measurement data obtained from a thru-reflect-line (TRL) calibration. The accuracy of the LRM calibration using the ANN-modeled load compares favorably to a benchmark multiline TRL calibration with an average worst-case scattering parameter error bound of 0.017 over a 40-GHz bandwidth.

INTRODUCTION

Multiline TRL is a highly accurate means of VNA calibration and is especially useful for on-wafer environments, since the characteristic impedance can be calculated from dimensional measurements of the standards, which simply consist of a number of transmission lines of varying line lengths and a highly reflective termination [1]. The disadvantages of this calibration method are that it requires a lot of area on the wafer, due to the numerous long lines required for an accurate calibration. Also, the different lengths of line necessitate changing the separation between probes during the calibration process. In contrast, the LRM calibration [2], which requires only a short transmission-line connection, a load, and a reflection, overcomes these limitations. Here, the reference impedance is set to that of the standard load. The impedance of many on-wafer loads, however, is non-ideal, which can lead to significant error in LRM calibrations. If the load is properly characterized, however, it is possible to perform an accurate on-wafer LRM calibration.

Once an imperfect load is characterized, we must decide whether to develop a model for the standard or to directly use the measurement data obtained from the benchmark calibration. Recently, Jargon et al. [3] applied artificial neural networks (ANNs) to improve the modeling of on-wafer open-short-load-thru (OSLT) standards. They showed that ANN models offer a number of advantages over the use of calibrated measurement data files or equivalent-circuit models, namely, the following: (1) they do not require detailed physical models, (2) calibration times can be reduced since only a few training points are required to accurately model the standards, (3) ANN model descriptions are much more compact than large measurement files, (4) ANN models trained on only a few measurement points can be much more accurate than direct calibrations when limited data are available, and (5) they are less susceptible to the noise inherent in measured data.

In this paper, we use a single-line TRL calibration to train an ANN model of the load for use with an on-wafer LRM calibration. Using a single-line TRL calibration enables us to build an effective model

* Work of the U.S. Government. Not subject to U.S. Copyright.

of the load using minimal area on the wafer. This methodology results in an LRM calibration with less overall error than that resulting from simply applying the single-line TRL calibration [4]. The following sections describe our implementation of ANNs and assess the accuracy of the LRM calibration using the ANN-modeled load.

LOAD MODELING

In this study, the LRM and multiline TRL standards and devices were constructed of coplanar waveguide (CPW) transmission lines fabricated from 1.5 μm gold conductors on a layer of 500 μm thick semi-insulating GaAs [5]; the gold center conductor was 73 μm wide, and was separated from the ground plane by 49 μm gaps. The five line standards included a 0.55-mm thru line and four additional lines that were 2.135, 3.2, 6.565, and 19.695 mm longer. All of the standards were measured using on-wafer probes. For each standard, we measured scattering parameters at 192 frequencies from 0.5 to 40 GHz.

In Figure 1, we plot measurements of magnitude and phase of the load’s reflection coefficients. They were determined by a TRL calibration using only the thru connection and the 2.135-mm line, and applying an impedance transformation to the calibration, which yielded the measured *S*-parameters referenced to 50 Ω [6]. Use of only a single line explains the inaccuracy at multiples of 26.65 GHz, where the difference in line lengths corresponds to a multiple of half a wavelength. The figure shows that the load deviates significantly from 50 Ω.

We then used an ANN to model the load. The ANN architecture used for this modeling was a feedforward, three-layer perceptron structure (MLP3) consisting of an input layer, a hidden layer, and an output layer. Such an ANN allows complex models of input-output relationships. According to [7], an MLP3 with one hidden sigmoidal layer is able to model almost any physical function accurately provided that a sufficient number of hidden neurons are available. ANNs learn relationships among sets of input-output data, which are characteristic of the device or system under consideration. After the input vectors are presented to the input neurons and the output neurons are computed, the ANN outputs are compared to the desired outputs, and errors are calculated. Error derivatives are then calculated and summed for each weight until all of the training sets have been presented to the network. The error derivatives are used to update the weights for the neurons, and training continues until the errors are less than prescribed values. In this study, we utilized software developed by Zhang et al. [8] to construct our ANN models.

The ANN for the load standard consisted of one input (frequency) and two outputs (the real and imaginary components) for the *S*-parameters. Based on previous experience [3], five neurons were chosen for the hidden layer. Figure 1 shows the magnitude and phase of the *S*-parameters of both measured and ANN-modeled data for the load standard. Notice that the ANN model for the load standards follows the trends of the measured data, but avoids both the spike near 26.65 GHz as well as scatter of the TRL-calibrated measurements. Whether or not this scatter is real, we see that ANNs follow general trends but omit noise, which is usually desirable in a model.

CALIBRATION COMPARISONS

First, two consecutive multiline TRL calibrations, using all five lines, were compared to assess the limitations on calibration repeatability caused by contact error and instrument drift. The technique of [9] was used to determine an upper bound on this repeatability error. Briefly, the comparison determines the upper bound for $|S'_{ij}-S_{ij}|$ for measurements on any passive device, where S'_{ij} are the scattering parameters of a device measured with respect to the first calibration and S_{ij} are the scattering parameters measured with respect to the second calibration. The bound is obtained from a linearization, which assumes the two calibrations are similar to the first order. The result, plotted as a solid curve in Figure 2, roughly indicates the minimum deviation between any pair of calibrations. The average of the worst-case error bounds for repeatability was 0.013.

We also compared the single-line TRL calibration, which was used to develop the ANN model, to the multiline TRL calibration. The result is plotted in Figure 2. Since we used only the 2.135-mm line standard, our calibration accuracy is poor near multiples of 26.65 GHz, where the difference in line lengths corresponds to a multiple of half a wavelength [1]. Otherwise the single-line TRL calibration is nearly as accurate as the multiline TRL calibration at most frequencies.

We assessed the accuracy of the LRM calibrations by comparing them to a 50 Ω multiline TRL calibration. First, we compared a simple LRM calibration, where the load is assumed to be ideal, to the multiline TRL calibration. Figure 2 illustrates a large difference since the reference impedance of the LRM calibration, which is equal to the impedance of the non-ideal load, deviates significantly from 50 Ω.

In order to assess the accuracy of the best LRM calibration, we compared the multiline TRL calibration to the LRM with a fully characterized load, which involved calibrating the load with the benchmark multiline TRL calibration and using the calibrated measurement data file to define the load. This comparison is once again shown in Figure 2. The average of the worst-case error bounds for this calibration was 0.011. Figure 2 also shows the worst-case error bounds for the LRM calibration based on the ANN-modeled load. Here, the average worst-case error bound was 0.017.

CONCLUSIONS

The use of ANNs to model on-wafer LRM load standards compares favorably to a benchmark multiline TRL calibration, with an average worst-case scattering-parameter error bound of 0.017 over a 40-GHz bandwidth. In our ANN model, we made use of five hidden neurons in the hidden layer of an MLP3 architecture.

ANN models are advantageous in that they do not require detailed physical descriptions and they eliminate noise inherent in measured data. They are also preferred over calibrated measurement files since they are much more compact in size. For example, the ANN model we developed for the load required 28 real-valued parameters to generate complex *S*-parameters as a function of frequency. In contrast, a single measurement file contains 576 real-valued numbers (192 frequency points plus the real and imaginary components at each point). We have also shown in previous work [3] that calibration times can be reduced when modeling standards using ANNs since only a few training points are required to accurately model them.

REFERENCES

[1] R. B. Marks, “A multiline method of network analyzer calibration,” *IEEE Trans Microwave Theory Tech* 39 (1991), pp. 1205-1215.

[2] D. K. Rytting, “Network analyzer error models and calibration methods,” 52nd ARFTG Conference, Short Course on Computer-Aided RF and Microwave Testing and Design, Rohnert Park, CA, Dec. 1998.

[3] J. A. Jargon, K. C. Gupta, and D. C. DeGroot, “Artificial neural network modeling for improved on-wafer OSLT calibration standards,” *Int J RF and Microwave CAE* 10 (2000), pp. 319-328.

[4] D. F. Williams, R. B. Marks, and K. R. Phillips, “Translate LRL and LRM calibrations,” *Microwaves & RF*, Feb. 1991, pp. 78-84.

[5] D. F. Williams, R. B. Marks, K. R. Phillips, and T. Miers, “Progress toward MMIC on-wafer standards,” *36th ARFTG Conf Dig*, Nov. 1990, pp. 73-83.

[6] R. B. Marks and D. F. Williams, “Characteristic impedance determination using propagation constant measurement,” *IEEE Microwave Guided Wave Lett* 1 (1991), pp. 141-143.

[7] F. Wang, V. K. Devabhaktuni, C. Xi, and Q. J. Zhang, "Neural network structures and training algorithms for RF and microwave applications," *Int J RF and Microwave CAE* 9 (1999), pp. 216-240.

[8] NeuroModeler, ver. 1.2, Q. J. Zhang and his neural network research team, Department of Electronics, Carleton University, Ottawa, Canada, 1999.

[9] D. F. Williams and R. B. Marks, "Comparison of on-wafer calibrations," *38th ARFTG Conf Dig*, Dec. 1991, pp. 68-81.

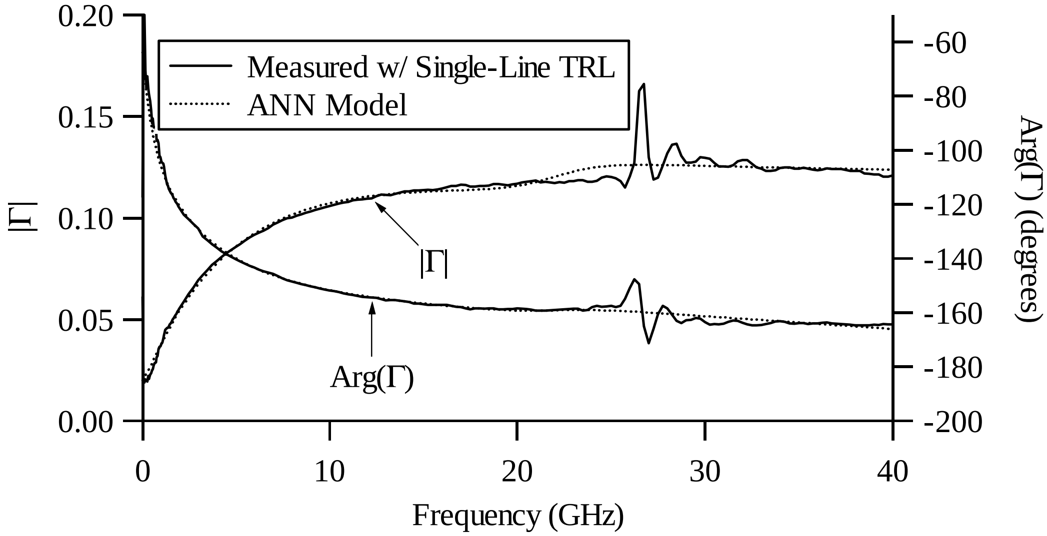

Figure 1. Magnitude and phase of the measured and modeled *S*-parameters of the load.

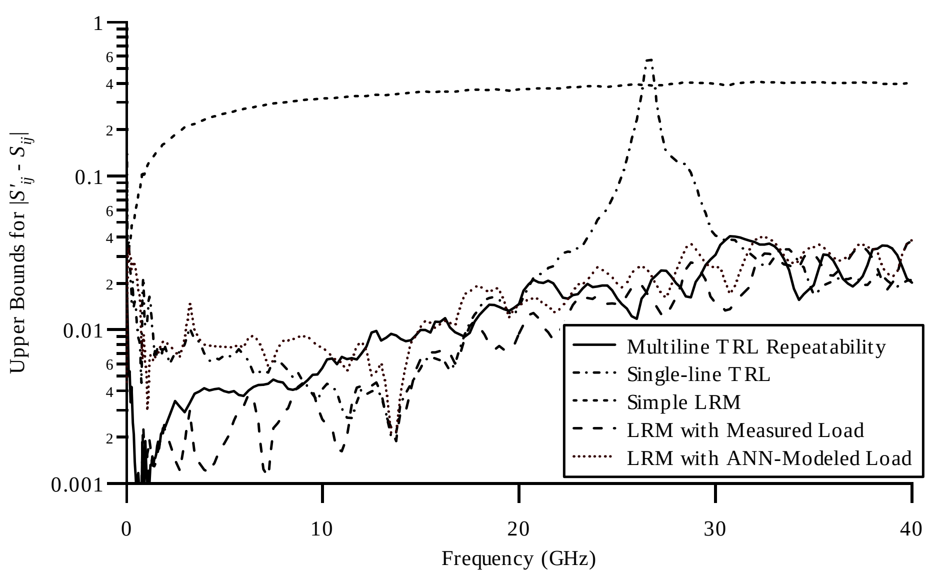

Figure 2. Worst-case error bounds between measurements of passive devices from LRM and TRL calibrations and the multiline TRL calibrations.